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UCSD

Generating and Using Local Solar Forecasts (from 5 Minutes to 72 Hours ahead)

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STATE OF CALIFORNIA ENERGY COMMISSION

DEPARTMENT OF ENERGY UNITED STATES OF AMERICA

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Motivation

- Central Station solar power plants rely oneither the Direct Normal Irradiance (DNI)or the Global Horizontal Irradiance (GHI) to produce power
- DNI is mostly affected by cloud cover, and to much lesser extent, by aerosol content
- Power plants with no thermal storage require short-term forecasts for optimal operation
- Ramp forecasts help optimize operations to avoid ramp rate violations, plant tripping, and deep discharges of storage systems
- Multiple temporal horizons are needed for regulation, operations, dispatching, scheduling (grid integration).

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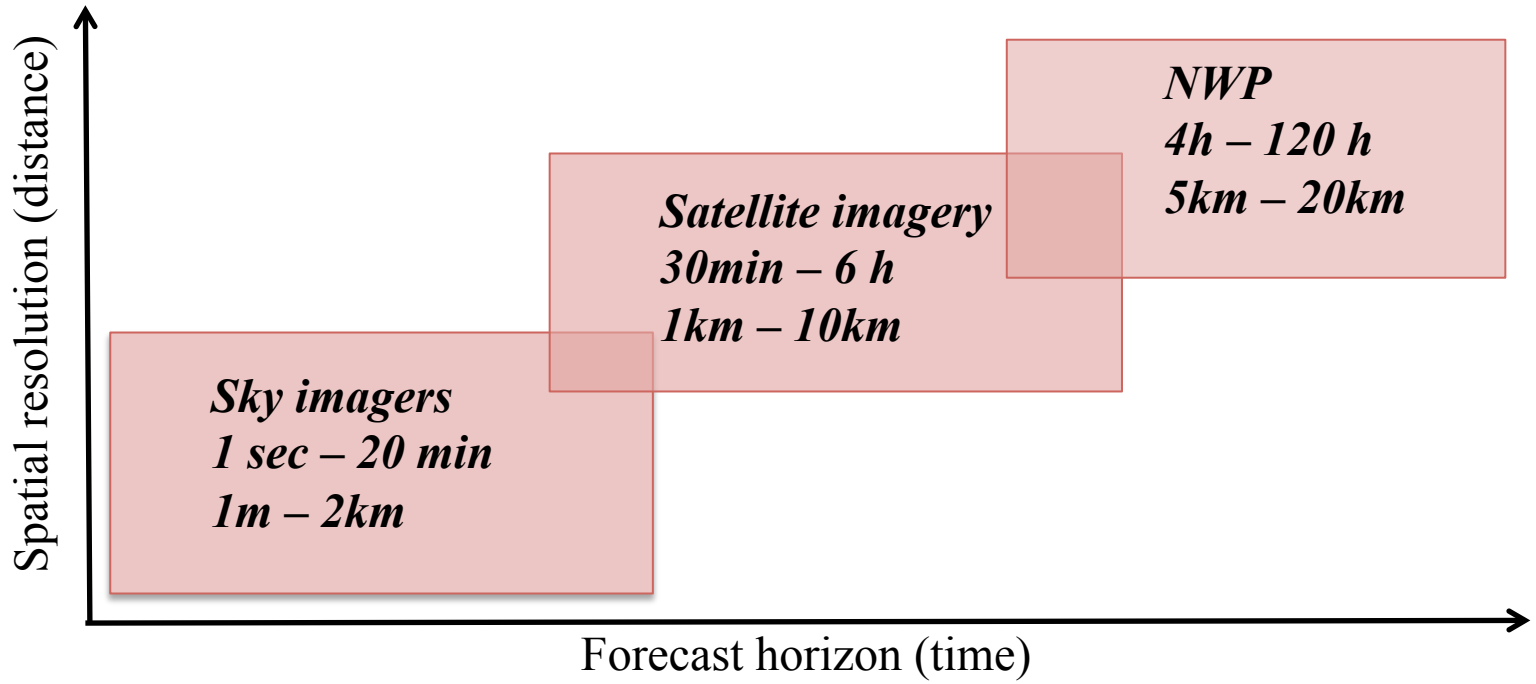
Solar forecasting



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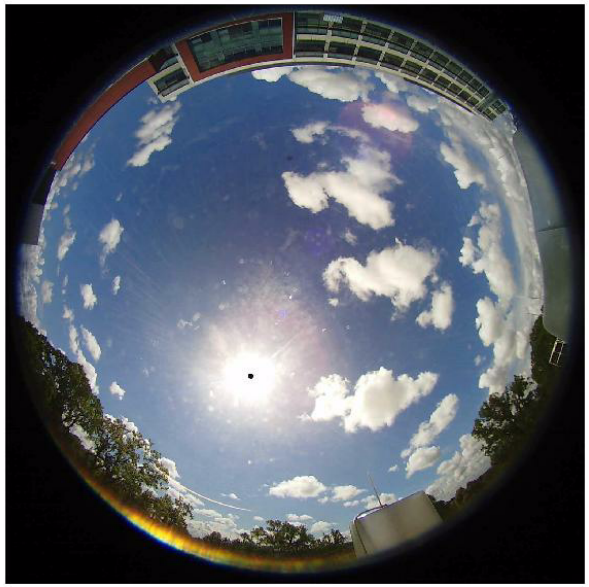
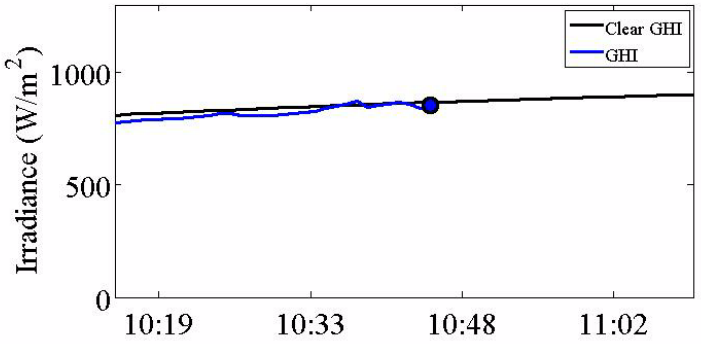
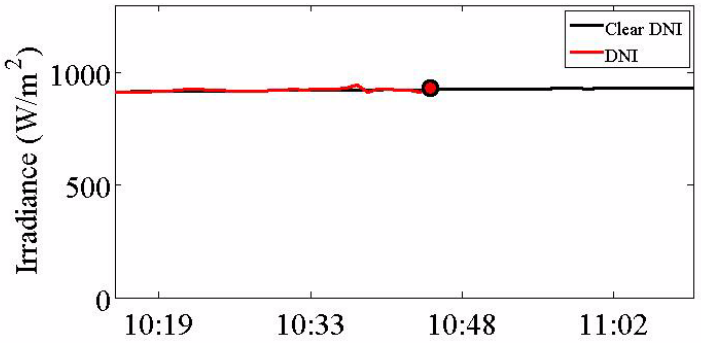
Clouds strongly influence solar irradiance at the ground level







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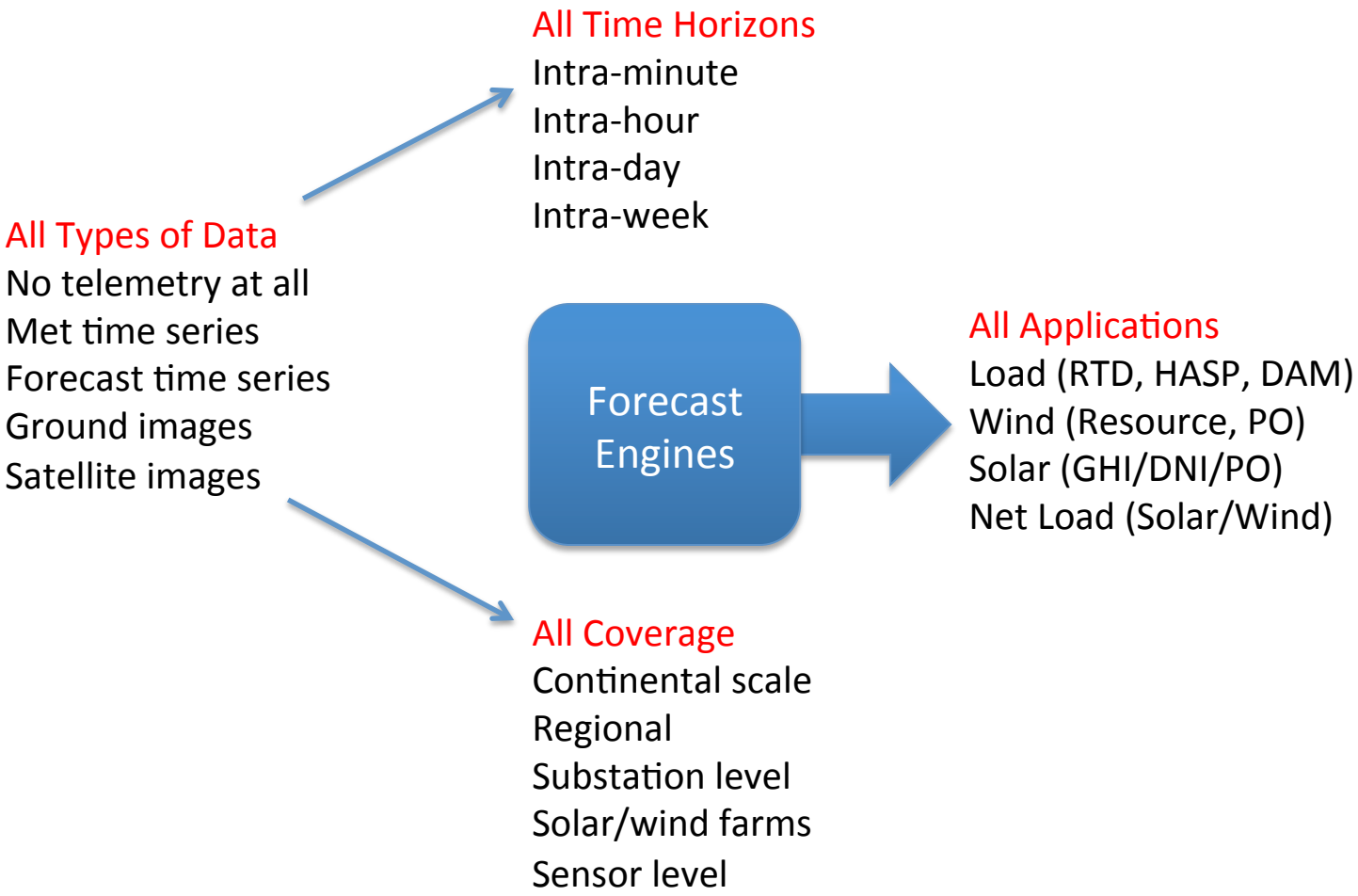
Multilayered Forecasting Engines



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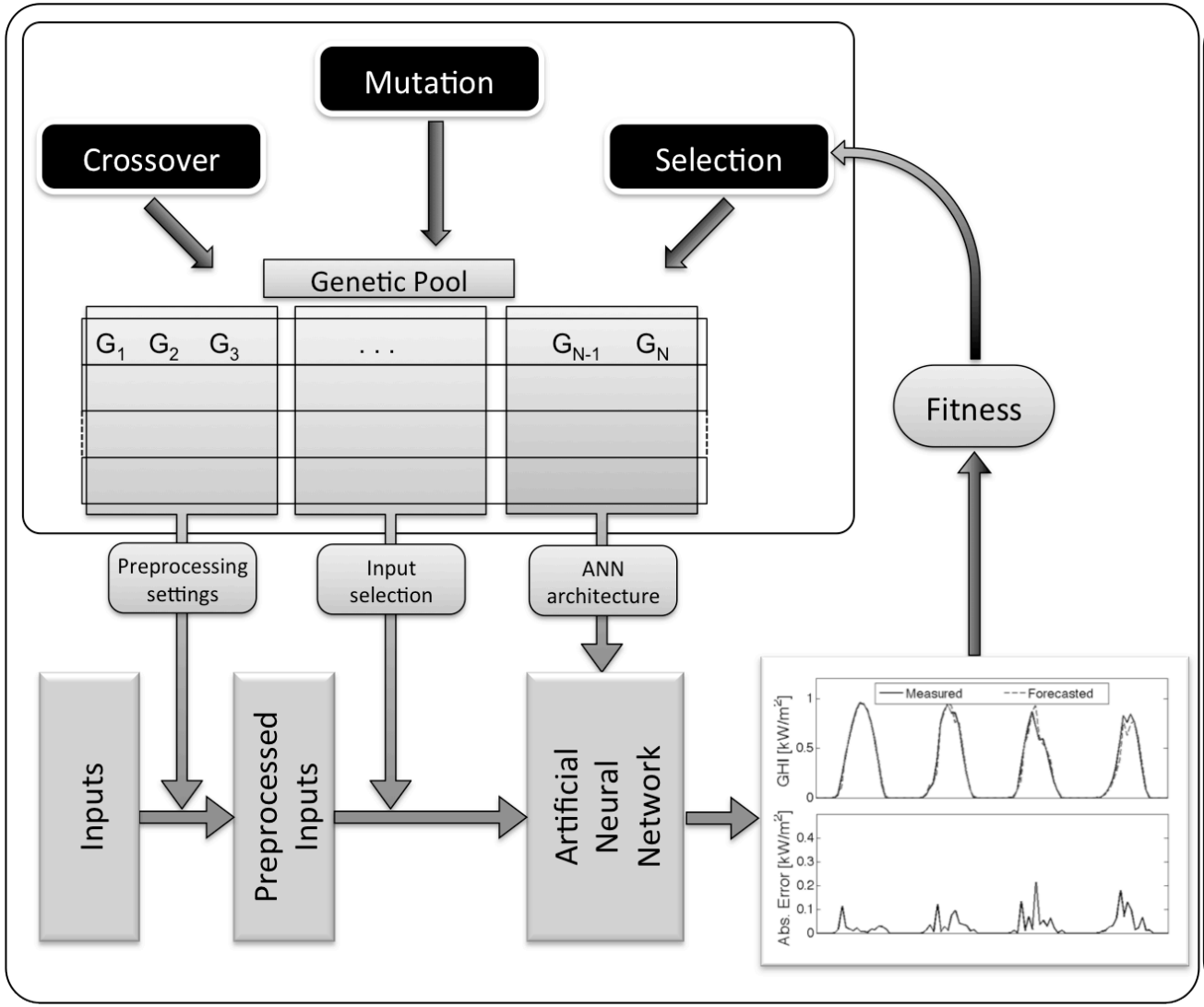
GA-optimized ANN-based Forecast Systems



The Genome specifies

- Which inputs are preprocessed, and how they are preprocessed (e. g. moving averages, fractional order derivatives, etc.);
- Which inputs are used in the ANN;
- The ANN architecture (number of layers, number of neurons, etc.)

The fitness:

- Statistical metrics (MSE, RMSE, MAE, R^2) of the forecasting error are used to determined the fitness of the model;
- The GA is advanced based on the selection, crossover and mutation operators.

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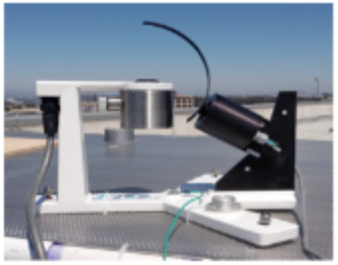
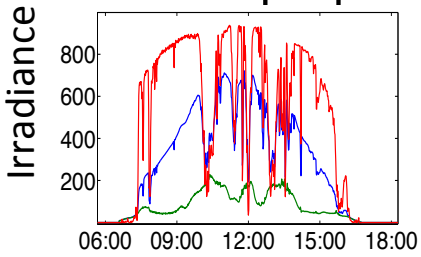
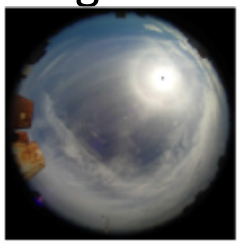
Intra-hour forecasts

Instrumentation

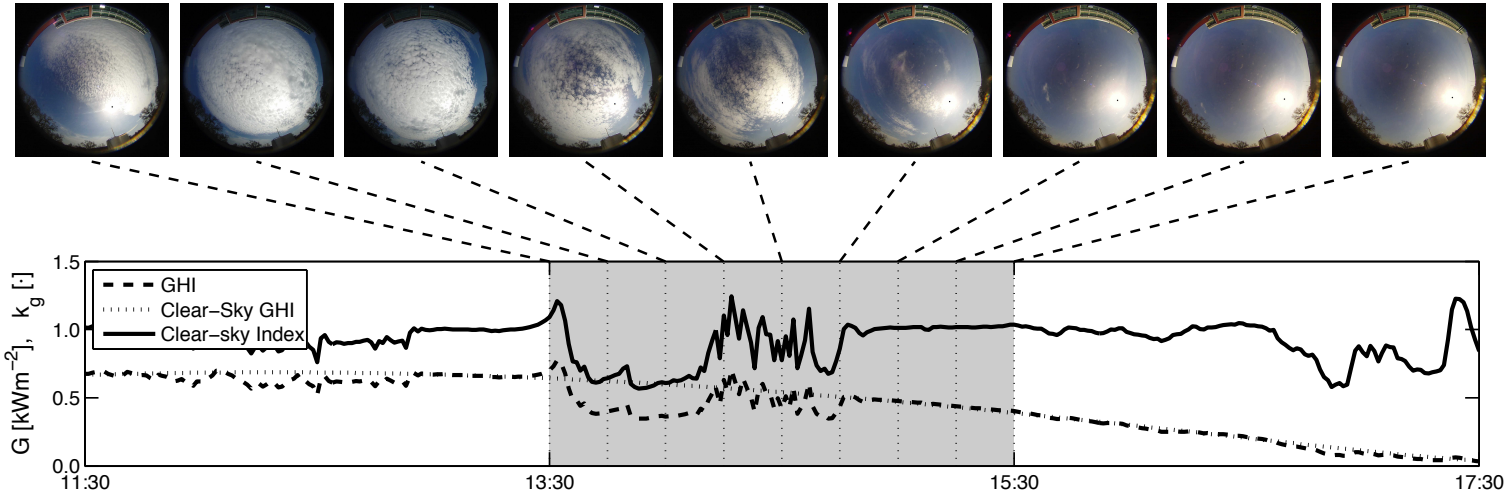


Data preprocessing





Model development



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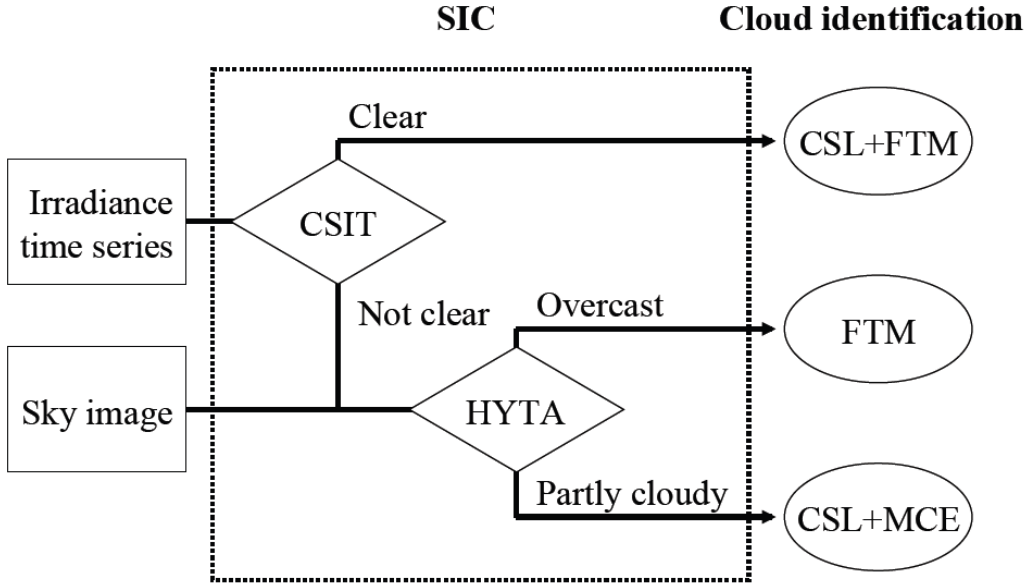
Smart Adaptive Cloud Identification System (SACI)

The SACI method was proposed to address the image glare as well as realize robust cloud detection performance based on three popular cloud detection method:

- Fixed threshold method (FTM)
- Minimum cross entropy method[1,2] (MCE)
- Clear sky library method[3] (CSL)



Schematic of smart adaptive cloud identification system (SACI[4]). SIC stands for smart image categorization algorithm.

[1] Li, C. H. and C. K. Lee, 1993: Minimum cross entropy thresholding. *Pattern Recognition*, **26**, 617- 625.
[2] Li, C. H. and P. K. S. Tam, 1998: An iterative algorithm for minimum cross entropy thresholding. *Pattern Recognition Letters*, **19**, 771-776.
[3] Ghonima, M. S., B. Urquhart, C. W. Chow, J. E. Shields, A. Cazorla, and J. Kleissl, 2012: A method for cloud detection and opacity classification based on ground based sky imagery. *Atmospheric Measurement Techniques Discussions*, **5**, 4535-4569.
[4] Y. Chu, L. Nonnenmacher, R.H. Inman, Z. Liao, H.T.C. Pedro and C.F.M. Coimbra (2014) "A Smart Image-Based Cloud Detection System for Intra-Hour Solar Irradiance Forecasts," Journal of Atmospheric and Oceanic Technology, Vol. 31, No. 9, pp. 1995-2007.

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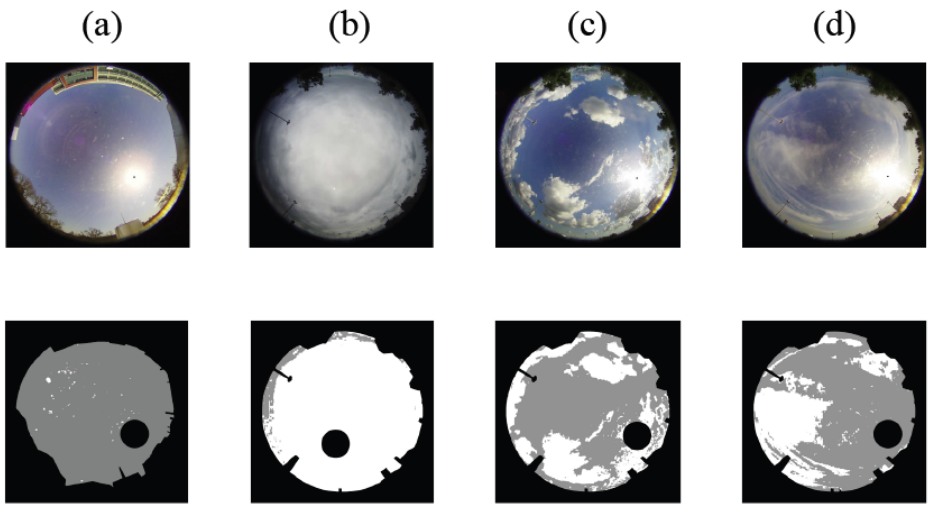
Cloud Detection Testing

	Ground truth	
Model detected	**Cloud**	**Sky**
Cloud	True positive (TP)	False positive (FP)
Sky	False negative (FN)	True negative (TN)

Accuracy=(TP+TN)/(TP+TN+FP+FN)



Accuracy	Merced			Folsom		
	Clear	Overcast	Partly cloudy	Clear	Overcast	Partly cloudy
FTM	0.60	0.96	0.81	0.55	0.94	0.89
MCE	0.53	0.94	0.82	0.65	0.92	0.88
CSL	0.92	0.43	0.87	0.95	0.50	0.91
SACI	**0.92**	**0.96**	**0.91**	**0.95**	**0.94**	**0.94**

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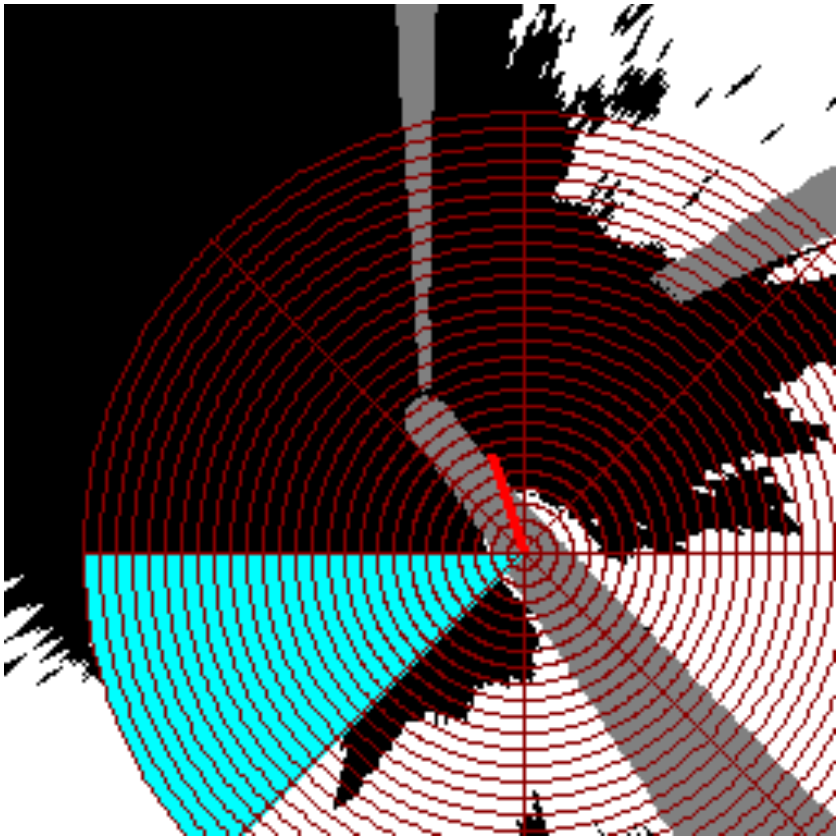
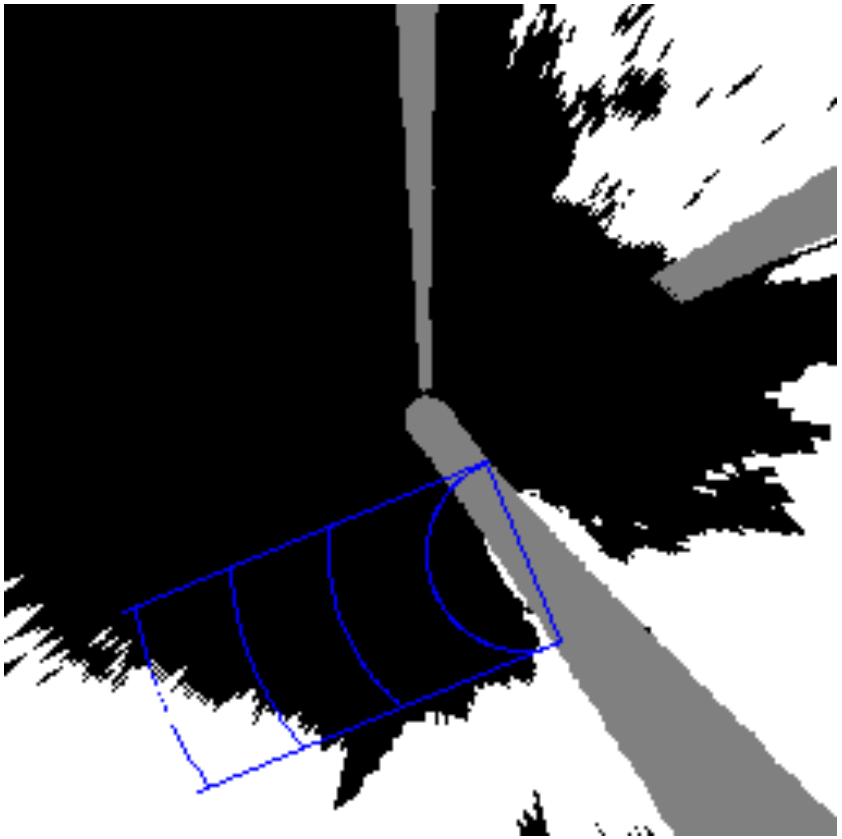
Sector and Ladder Methods

(2011/10/05)



Sector method over Cloud Index (CI) image for Cloud Tracking.
PIV orientation is also shown (red line).

(2011/10/05)



Ladder method over Cloud Index (CI) image for DNI Forecasting.

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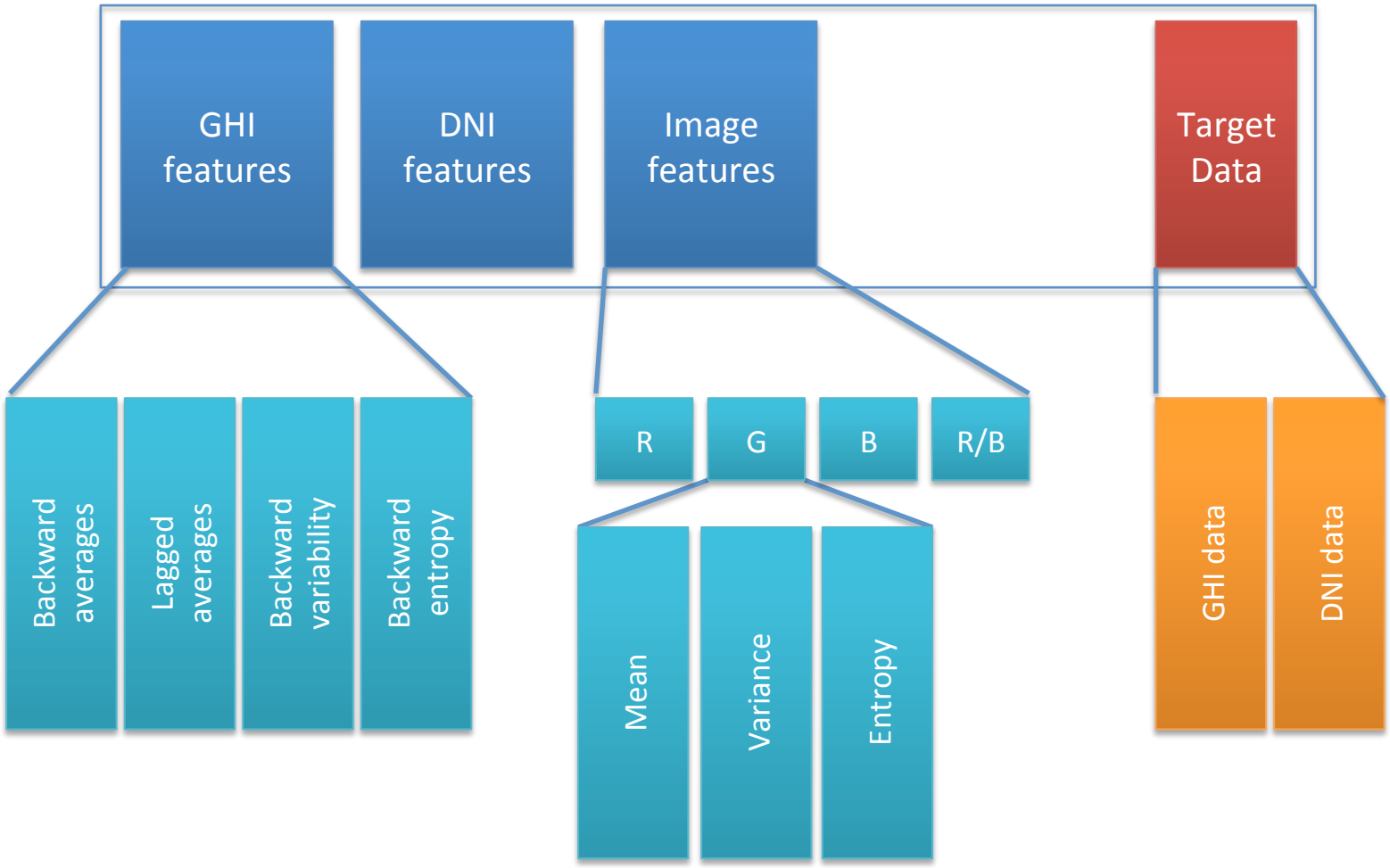
Assemble all features into a database



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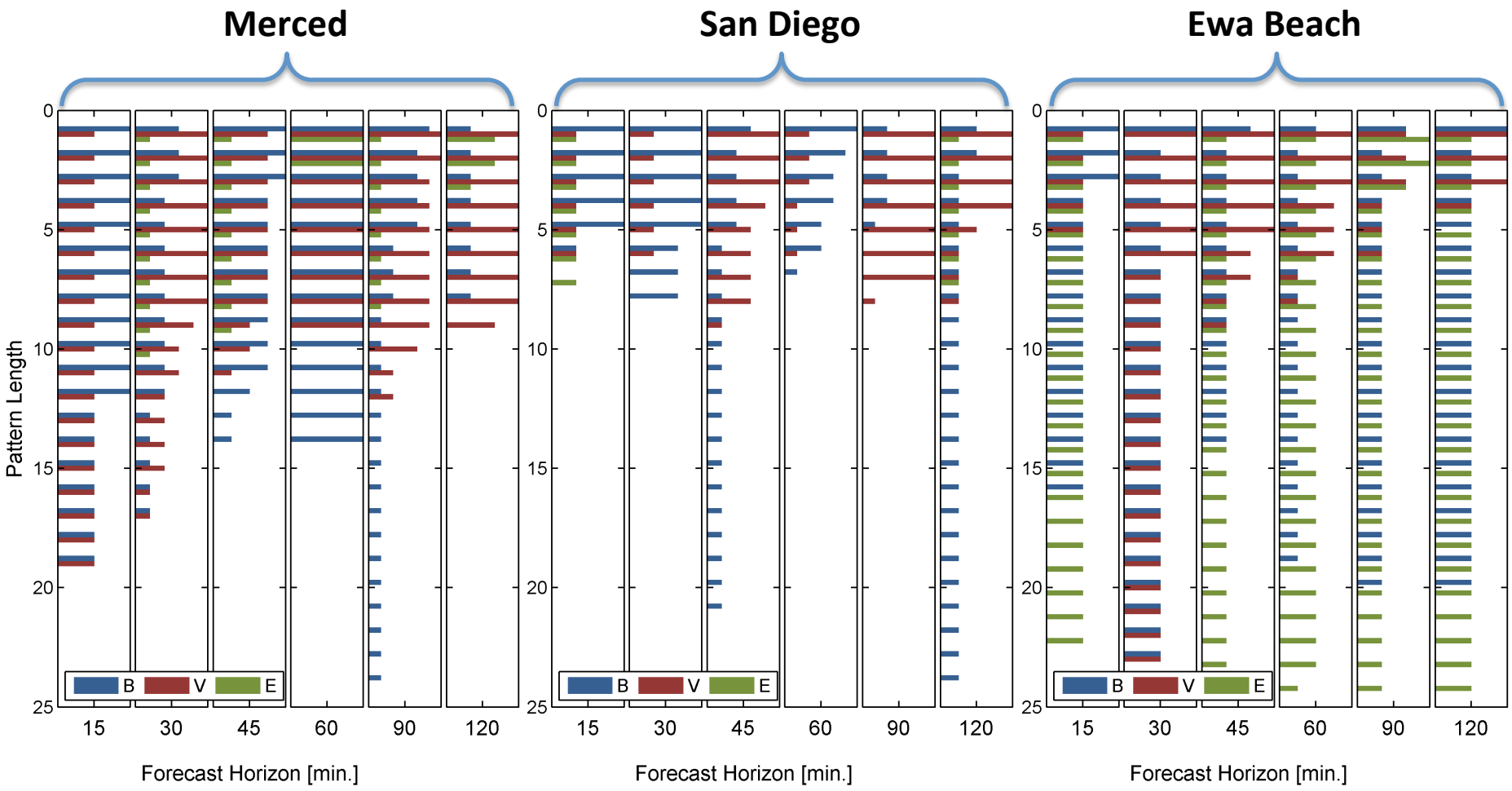
Classification of Solar Microclimates



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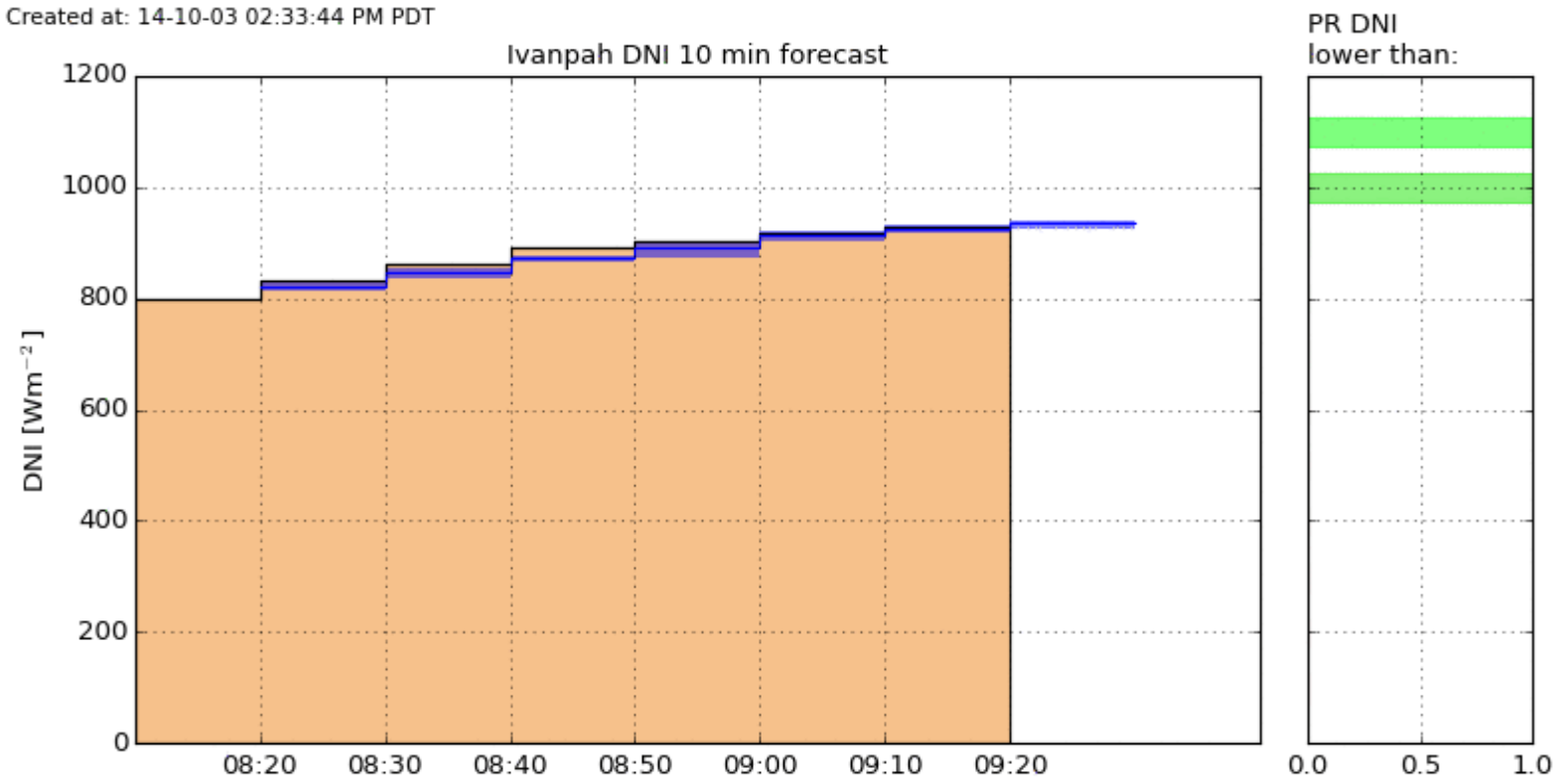
Short-Term Probabilistic Forecasts



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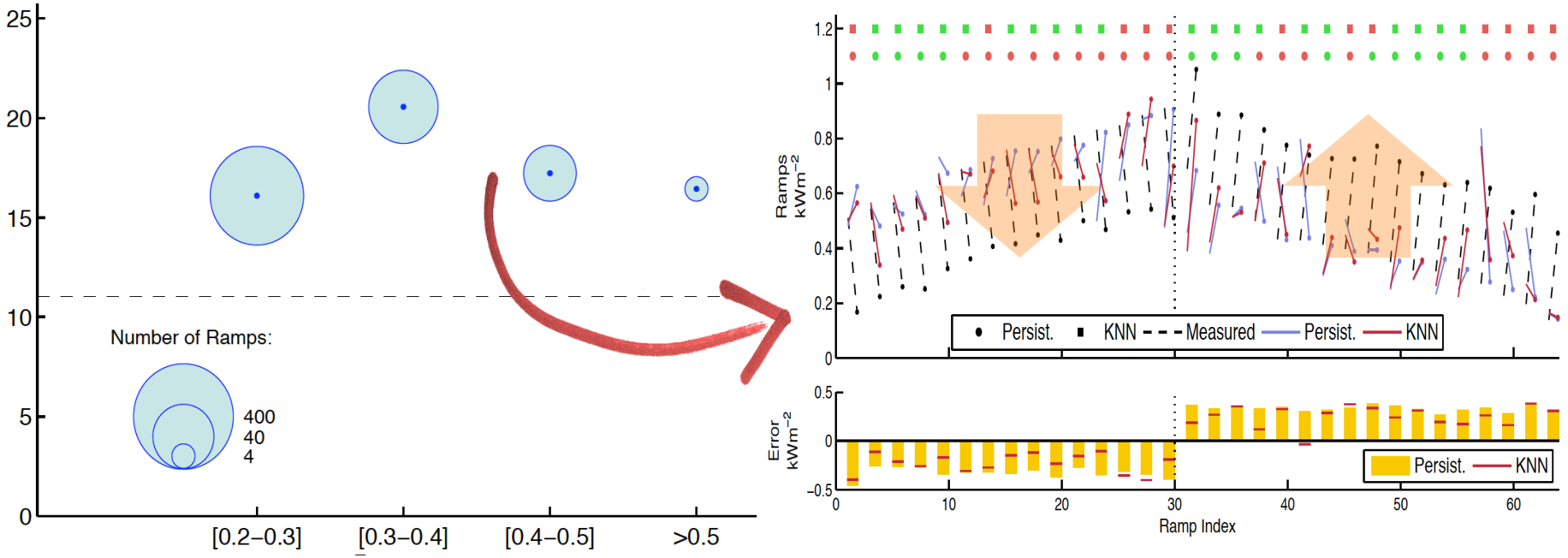
Forecasting Large Ramps



Left: Forecast skill (%) versus large ramps. The dashed line indicates forecast skill when all data are taken into account. The blue dots show forecast skill for ramps ($|GHI_{i+1}-GHI_i|$ in kWm^{-2}) in the range indicated in the x-axis. The size of the circle indicates the number of ramps in that range. **Right top:** Individual ramps in the range [0.3-0.4] kWm^{-2}. The dashed black line show the actual ramps and the blue and red lines show the forecasted ramps. The green (red) symbols at the top show if the forecast predicted correctly (incorrectly) the ramp signal. **Right bottom:** The forecast error for individual ramps.

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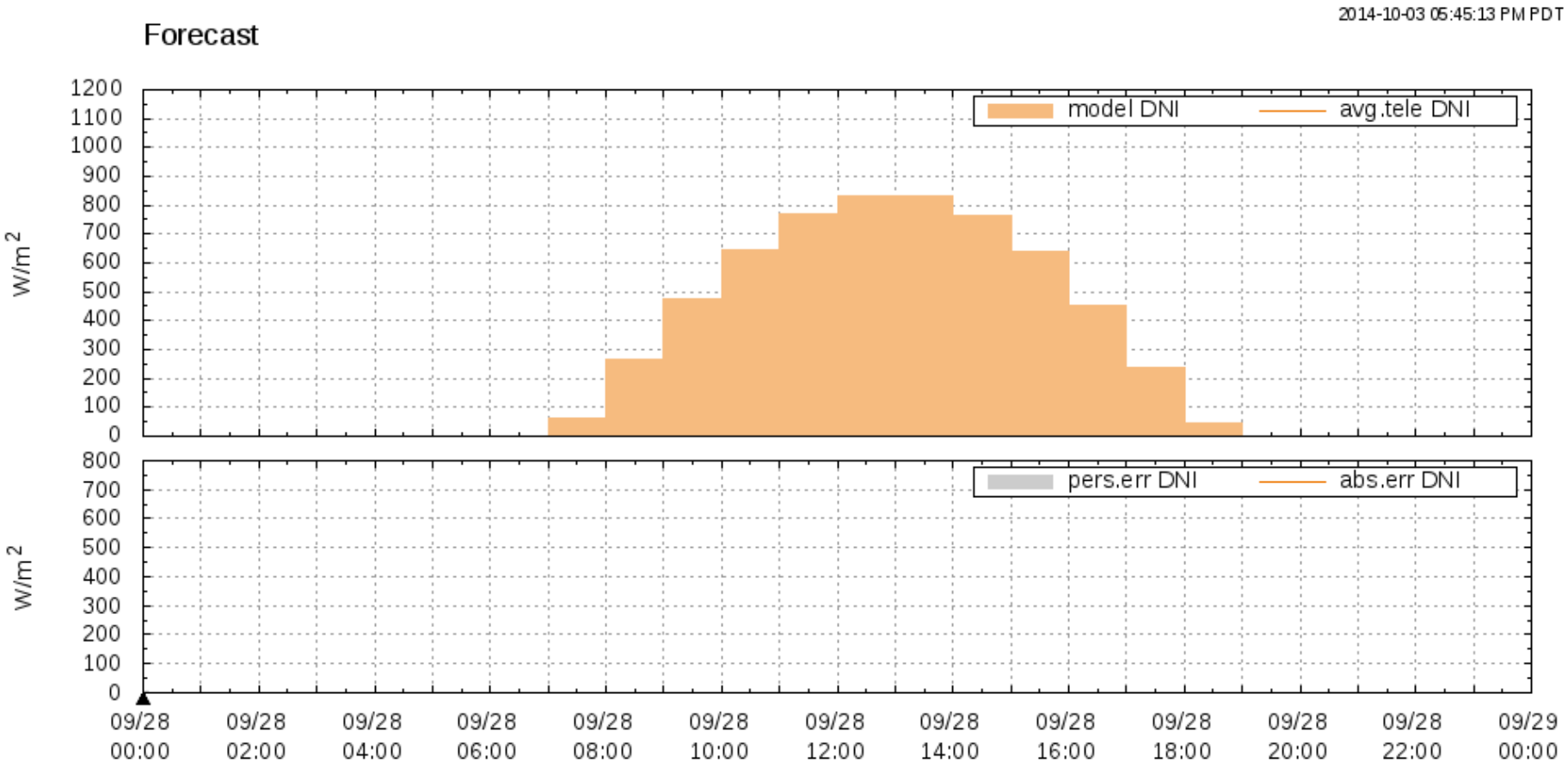
Concatenated Forecasts (DNI)
5 minutes to 72 hours ahead



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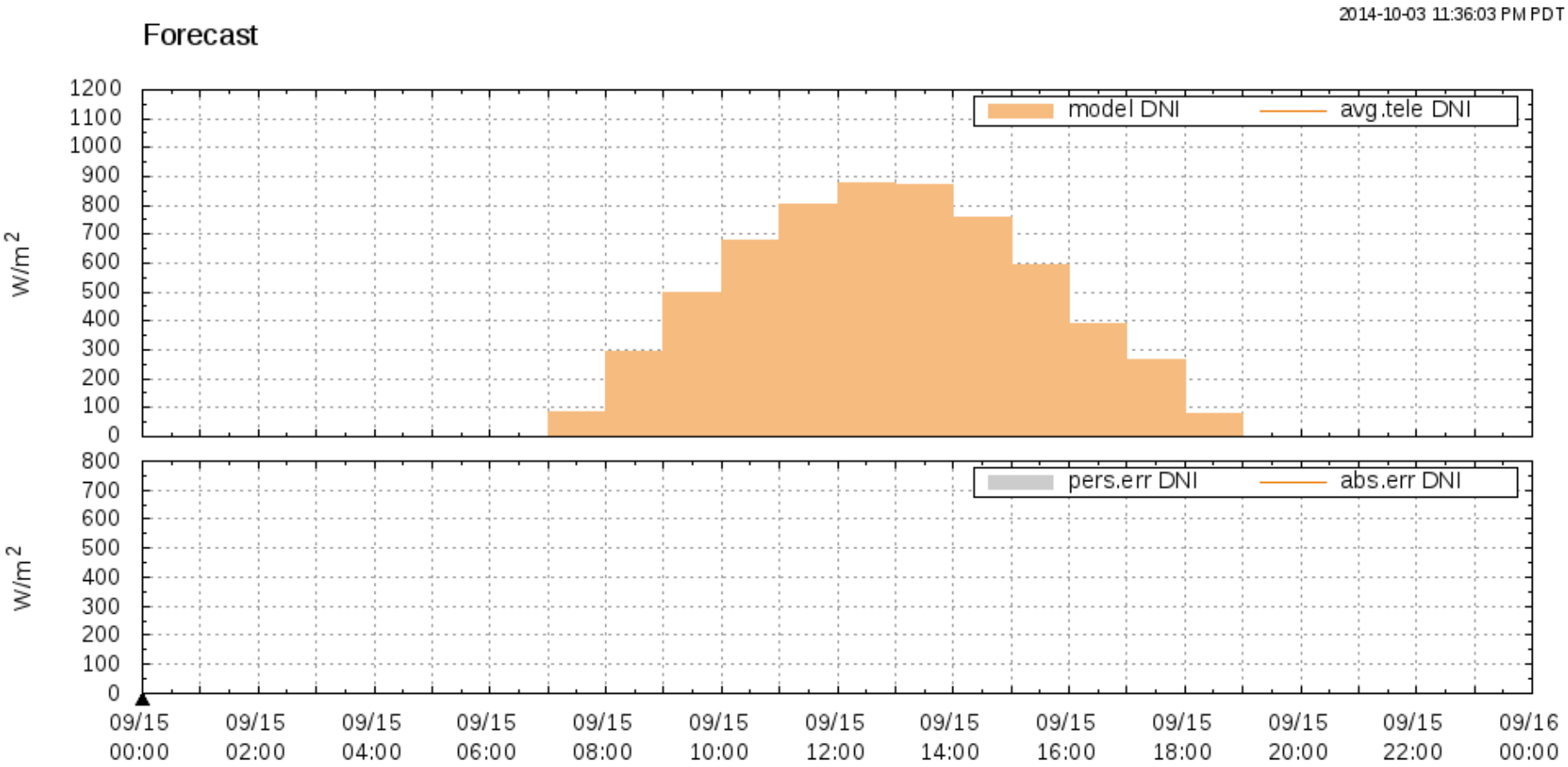
Concatenated Forecasts (cont.)
5 minutes to 72 hours ahead



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Some Remarks

- Evolutionary forecast engines offer robust forecasting skills using the most diverse sets of inputs: no exogenous variables, no telemetry, with or without image processing, remote sensing and/or meteorological data, etc. Attention needs to be paid to the complexity of the engine and latency issues, so all our forecasts are tested in real-time.

- Smart hybrid methods that combine ground telemetry with remote sensing and NWP offer the highest fidelity forecasts for all time horizons

- Our methods provide substantial in predicting the direction and magnitude of ramps, which is critical for optimal integration.

- Forecasting solutions with positive skills in the range 10-25% are operational and robust for both GHI and DNI for horizons ranging from 5 to 72 hours ahead. For some horizons, skills above 50% are possible.

- Clustering techniques can improve substantially the quality of the forecasts

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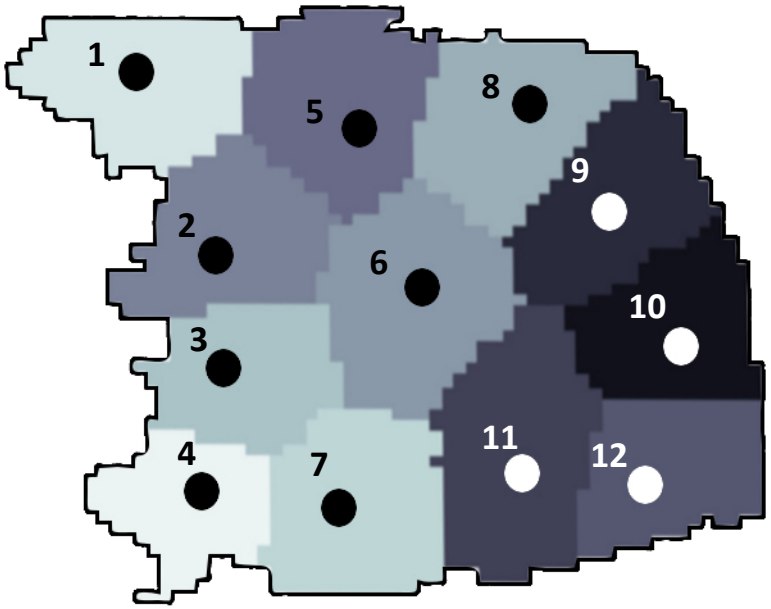
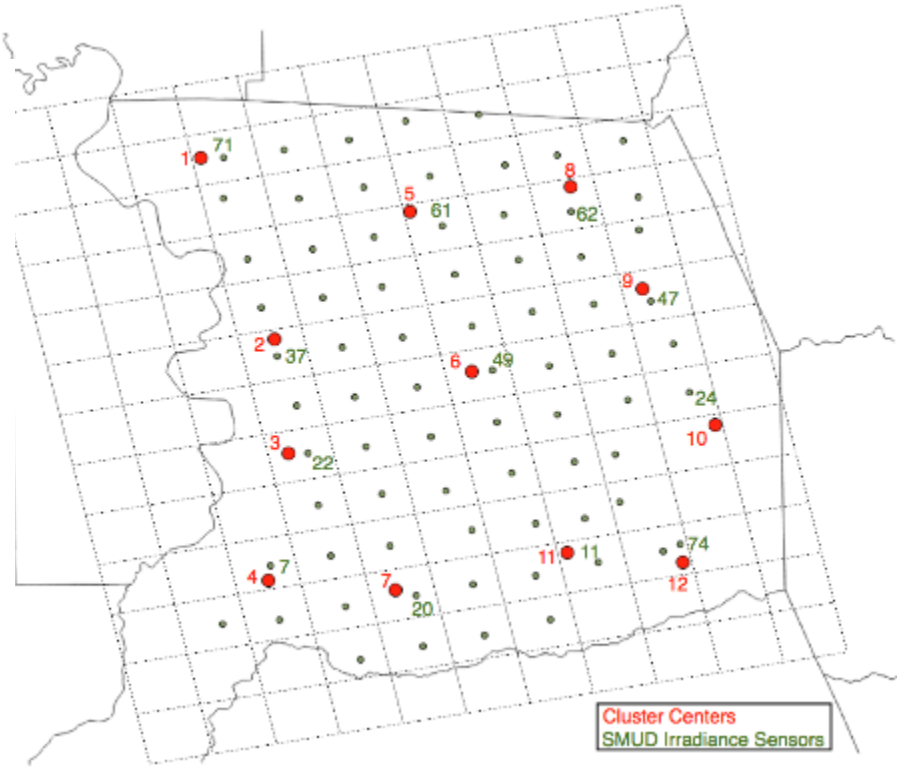
Distributed forecasts

- We used cluster analysis to find 12 locations that represent the GHI over the entire SMUD region

Clusters and cluster centers



SMUD's sensor network



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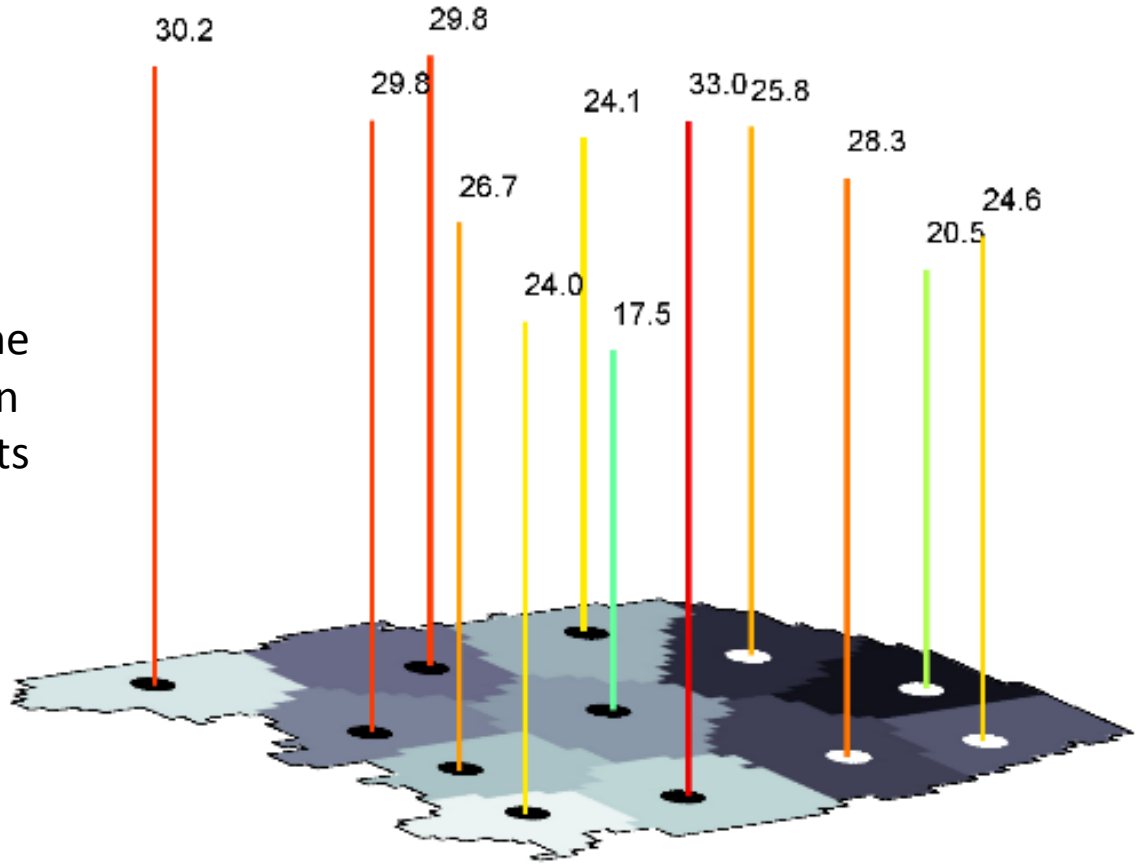
Clustering-Based Real-Time Reforecasts for Distributed Generation

Forecast skill improvement (% of RMSE reduction) for the **Satellite+NAM reforecasts** in comparison to NAM forecasts



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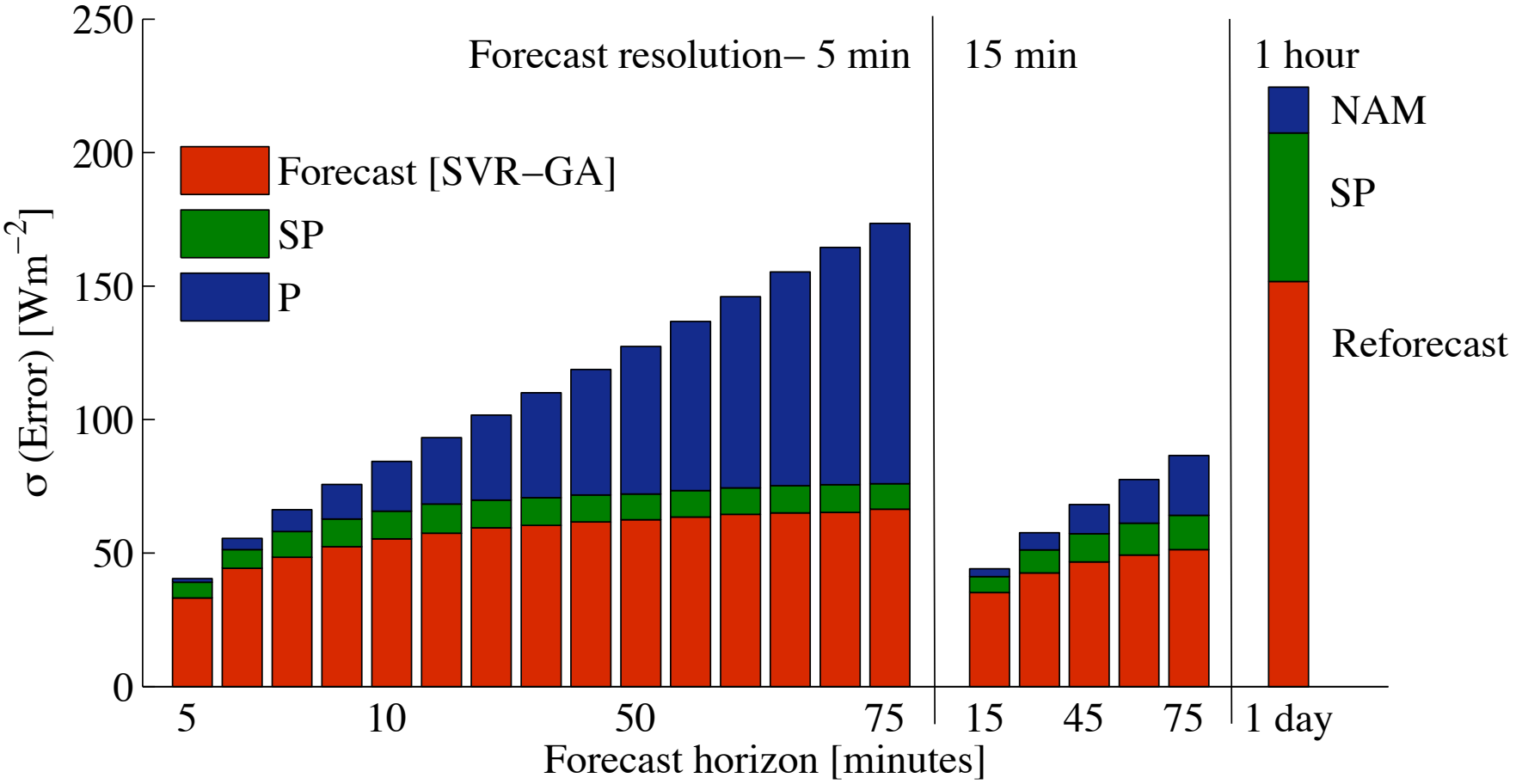
Summary of real-time, reforecasting improvements



A. Kaur, L. Nonnenmacher, H.T.C. Pedro and C.F.M. Coimbra, "Benefits of solar forecasting for energy imbalance market". [Submitted]